Tuning Multi-Objective Optimization Algorithms for Cyclone Dust Separators

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ABSTRACT

Cyclone separators are filtration devices frequently used in industry, e.g., to filter particles from flue gas. Optimizing the cyclone geometry is a demanding task. Accurate simulations of cyclone separators are based on time consuming computational fluid dynamics simulations. Thus, the need for exploiting cheap information from analytical, approximative models is evident. Here, we employ two multi-objective optimization algorithms on such cheap, approximative models to analyze their optimization performance on this problem. Under various limitations, we tune both algorithms with Sequential Parameter Optimization (SPO) to achieve best possible results in shortest time. The resulting optimal settings are validated with different seeds, as well as with a different approximative model for collection efficiency. Their optimal performance is compared against a model based approach, where multi-objective SPO is directly employed to optimize the Cyclone model, rather than tuning the optimization algorithms. It is shown that SPO finds improved parameter settings of the concerned algorithms and performs excellently when directly used as an optimizer.

Categories and Subject Descriptors

G.1.6 [**Mathematics of Computing**]: Optimization

General Terms

Algorithms, Experimentation

Keywords

Evolutionary Multi-objective Optimization, Parameter Tuning, Cyclone Optimization Problem

1. INTRODUCTION

Filtering dust particles from flue gas is a challenging task. Environmental consequence, governmental limitations, cost of operation, high temperature, and varying pressures increase the need for efficient filtering devices. Cyclone dust separators are frequently applied for this purpose since they combine low costs with robustness against high temperature or pressures.

The main quality indicators of a cyclone are the fraction of particles filtered from the gas, i.e. the Collection Efficiency (CE), as well as the Pressure Drop (PD). While CE reflects how well the cyclone solves its main task, PD is the main impact on operational cost. PD and CE may be conflicting, i.e., ideal PD will not coincide with ideal CE. They are heavily influenced by the choice of several geometrical design parameters, like height or diameter of a cyclone. This results into a Multi-objective Optimization (MO) problem, the so called Cyclone Optimization Problem (COP).

The quality of a cyclone may be evaluated with expensive Computational Fluid Dynamics (CFD) simulations or estimated with analytical, approximative models.

This study analyzes the performance of MO algorithms based on an analytical model of the cyclone. This allows for extensive tuning and comparisons, which may be used to parameterize algorithms used in future studies where the more expensive CFD simulations are employed.

Hence, the main goals of this study are:

- Determine performance of MO algorithms with default parameters.
- Tune the employed MO algorithms to determine good parameter settings and guarantee a fair comparison.
- Test the advantage of employing surrogate models in the MO.
- Validate results with a different model.

The remainder of this work is structured as follows. Section 2 introduces the optimization problem as well as the underlying analytical models for cyclone dust separators. Section 3 describes multi-objective optimization and related methods. After that, an empirical optimization study regarding the introduced problem is described in Sec. 4, including experimental setup as well as description and discussion of results. A final summary as well as an outlook on future research directions is given in Sec. 5.

2. CYCLONE OPTIMIZATION

2.1 Problem Description

Cyclones are frequently used devices to separate solid particles from a gas phase. Pollution and emission regulations compelled engineers to optimize the cyclone design. Cy-

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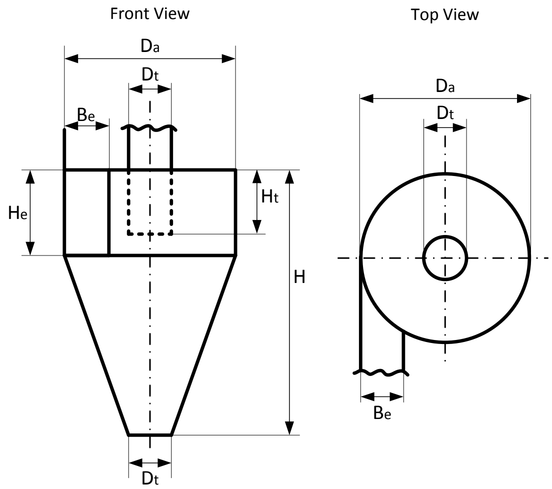

Figure 1: Schematic representation of a cyclone dust separator.

Table 1: Table of fluid, particle and geometrical parameters used in the experiments. Most values are taken from an example by Löffler [9].

Parameter	Symbol	Default	Unit
Geometrical Parameters			
Cyclone diameter	D_a	1260	mm
Cyclone height	H	2500	mm
Outlet pipe diameter	D_t	420	mm
Outlet pipe immersion	H_t	640	mm
Inlet height	H_e	600	mm
Inlet width	B_e	200	mm
Fluid/Particle Parameters			
Viscosity	μ	$18.5 \cdot 10^{-6}$	$Pa \cdot s$
Flow Rate	V_p	5000	$\frac{m^3}{h}$
Gas density	ρ_f	1.204	$\frac{kg}{m^3}$
Particle density	ρ_p	2000	$\frac{kg}{m^3}$
Particle concentration	c_e	50	$\frac{g}{m^3}$
Output values			
Pressure Drop	PL	1626	Pa
Collection Efficiency	CE	0.89	–

clones exist in different shapes but the reverse flow cyclone represented in Fig.1 is the most common design in industry. The principle of cyclone separation is simple: the gas-solid mixture enters at the top section tangentially. The cylindrical body induces a spinning. Centrifugal force separates the dust from the gas stream: the dust is moved to the walls of the cylinder and down the conical section to the dust outlet while the gas exits through the outlet pipe. The efficiency of this process is mainly influenced by the geometric shape. A set of seven geometrical parameters like height or diameter allows to describe a cyclone as shown in Fig. 1. Several characteristics constitute a COP.

1. Geometric shape: Seven geometric parameters describe the cyclone as shown in Fig. 1.
2. Fluid/Gas properties: Parameters like viscosity or density describe the carrier substance
3. Particle properties: Particle composition is described by density, concentration, and size distribution

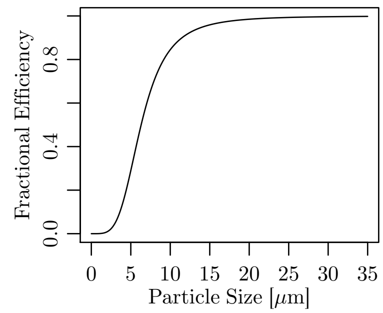

Figure 2: Fractional efficiency curve.

4. Collection Efficiency (CE): Amount of particles filtered from the gas
5. Pressure Drop (PD): Difference in pressure between inlet and outlet

The default values used in our experiments for these parameters are listed in Table 1. PD and CE are the main criteria used to evaluate cyclone performance. Both are functions of the cyclone dimensions. The goal of cyclone design is to maximize CE and to minimize PD by adjusting the geometric parameters.

2.2 Models

2.2.1 Collection Efficiency

Separation of particles inside a cyclone is a result of the forces acting on them. There are basically two concepts to calculate the CE of cyclones in the literature: The "equilibrium-orbit" models and the "time-of-flight" models. We use two different kinds of approaches.

The Barth model: Barth [1] developed the original "equilibrium-orbit" model. There are two forces acting on a particle rotating in the cyclone body: the centrifugal force acting towards the wall and a drag acting towards the outlet pipe. Equating these forces, Barth calculates the so called cut size x_{50}, where drag and centrifugal force are equal. Here, 50% of the particles are collected. Smaller particles are collected with lower efficiency, larger with higher efficiency. Once we have the cut size, we can fit a fractional efficiency curve through it. For high concentrations of dust, the Barth model is often corrected with an approach to model mass loading effects: the concept of a "critical load", first introduced by Muschelknautz [11]. The optimization problem based on this model will be referred to as COP1.

The model of Mothes and Löffler: Mothes and Löffler [10, 9] present a model based on differential mass balances which are formulated for four zones in the cyclone. This model is a composition of the "equilibrium-orbit" and "time-of-flight" models. "Time-of-flight" models determine whether the particle has time to reach the wall. The optimization problem based on this model will be referred to as COP2.

Both models include the main cyclone parameters and calculate a fractional efficiency curve $T(x)$ that assigns an efficiency to the particle diameter as shown in Fig. 2. Larger particles are collected more efficiently than smaller particles. The overall efficiency can be calculated by integrating the fractional efficiency curve over the particle size distribution according to:

$$E = \int_{x_{min}}^{x_{max}} T(x) q_e(x) dx = \sum_{x_{min}}^{x_{max}} T(\tilde{x_i}) \Delta Q_e(x_i) \quad (1)$$

where x_{min} is the lower bound of the particle size, x_{max} is the upper bound of the particle size, $\tilde{x_i}$ is the mean particle size, $\Delta Q_e(x_i)$ is the change in distribution of particle sizes and $q_e(x) = \frac{\Delta Q_e(x_i)}{\Delta x_i}$. In the experiments, values for $\Delta Q_e(x_i)$ are taken from an example by Löffler [9].

2.2.2 Pressure Drop according to Muschelknautz

PD is defined as the difference in pressure Δp between two points of a fluid carrying body. It occurs with frictional forces and relates directly to operational cost. Therefore, an exact prediction is very important. Total PD equals to:

$$\Delta p = \frac{\rho}{2} v_i^2 (\xi_{e-a} + \xi_{a-i} + \xi_{i-m}) \qquad (2)$$

where ξ_{e-a}, ξ_{a-i} and ξ_{i-m} are friction coefficients for the loss within inlet, cyclone body and outlet pipe respectively. $\frac{\rho}{2} v_i^2$ is the relationship between pressure and velocity. This model is used in both COP1 and COP2.

2.3 The Cyclone Optimization Problem

In this paper, two different COP's are solved, COP1 and COP2. Both depend on analytical models and correspond to the geometrical description in Fig. 1 as well the default parameters in Table 1. The fluid parameters are assumed to be constant for the given problems. The six geometrical parameters are to be chosen to yield optimal CE and PD, yielding a bi-objective problem. PD will be calculated as described in Sec. 2.2.2. In COP1, the CE will be calculated with the model introduced by Barth [1]. while the model by Mothes and Löffler [10, 9] is involved in COP2.

2.4 Previous Research

Ravi et al. [15] used the Non Dominated Sorting Genetic Algorithm NSGA to optimize an analytical model for cyclone dust separators by Mothes and Löffler [10, 9]. Elsayed and Lacor [5] optimized four geometrical parameters using computational fluid dynamics CFD models and a model by Barth [1]. They minimized PD only, using the response surface methodology. Pishbin and Moghiman [13] optimized seven geometry parameters with a genetic algorithm, minimizing PD and maximizing CE. They used a CFD model to construct the fitness function. The bi-objective problem was transferred to a single-objective problem using weights. Elsayed and Lacor [6] minimized PD and cut-off diameter. They used a Pareto optimization approach, utilizing a Radial Basis Function Neural Network RBFNN. A similar approach was taken by Safikhani et al. [16].

The herein presented work uses the analytical model by Barth [1] and Muschelknautz [12] to tune state-of-the-art MO algorithms. The tuned algorithms are then tested with the model by Mothes and Löffler [9]. Multi-objective Sequential Parameter Optimization [17] is compared to the tuned MO algorithms.

3. MULTI-OBJECTIVE OPTIMIZATION

A multi-objective optimization problem can be defined by a function

$$f : A \subset \mathbb{R}^n \longrightarrow \mathbb{R}^m, \quad f(x) = (f_1(x), \dots, f_m(x)),$$

with $x \in \mathbb{R}^n$, and the feasible set A. The common way to handle multi-objective optimization problems is Pareto optimization based on the concept of Pareto-dominance. One solution $x \in A$ is said to (Pareto-) dominate ($\prec$) another solution $y \in A$, if the following holds:

$$x \prec y \quad \text{iff} \quad \forall i: \; f_i(x) \leq f_i(y) \quad \wedge \quad \exists j: \; f_j(x) < f_j(y)$$

(for $i, j \in \{1, \dots, m\}$). Consequently, the set $\{x \in A \mid \nexists y \in A: \; y \prec x\}$ is called the Pareto-set, while the corresponding set under mapping f is called the Pareto-front.

3.1 Algorithms

Evolutionary Algorithms (EA) have become a standard tool for solving MO problems, and are here termed Evolutionary Multi-objective Optimization Algorithms (EMOA). These algorithms are based on sets of solutions. This coincides well with the challenge of finding a set of solutions in MO problems.

One of the most popular algorithms is the Non-dominated Sorting Genetic Algorithm (NSGA-II) [4]. In this algorithm, individuals are first ranked by non-dominated sorting. To select from a set of equally ranked non-dominated individuals and preserve diversity, NSGA-II employs crowding distance. Crowding distance measures the average length of a cuboid spanned by the nearest neighbors of the solution for which the measure is computed.

Whereas NSGA-II uses crowding distance as an indicator of quality, other methods use the hypervolume, i.e. the space covered by a Pareto front with respect to a predefined reference point. Maximizing the hypervolume pushes solutions towards the desired objective values. Moreover, the hypervolume rewards a high diversity of solutions, i.e. a wide spread, and a regular distribution of solutions along the border to the non-dominated area. One of the techniques employing hypervolume maximization is the S-Metric Selection EMOA (SMS-EMOA) (cf. Beume et al. [3]).

In case of expensive optimization problems, it is a standard approach to reduce the number of target Function Evaluations (FE) by shifting the load to surrogate models. Several approaches in MO employ surrogate modeling. An overview is given by Knowles and Nakayama [8].

Sequential Parameter Optimization (SPO) [2] provides a flexible framework for surrogate model based optimization. Recently, SPO has also been extended to MO [17, 18], making use of various models as well as state-of-the-art MO algorithms like SMS-EMOA and NSGA-II. Hence, multi-objective SPO (MSPO) can directly solve the COP.

3.2 Tuning

Every optimization algorithm has parameters which influence the optimization performance. Tuning these parameters towards optimal performance is thus, again, an optimization problem. Tuning may be done for several reasons. Firstly, it allows to find better parameter settings thus leading to improved algorithms which solve the problem better. Secondly, tuning may yield additional understanding of the optimization algorithms. Finally, tuned algorithms allow for a fair comparison. That is, the good/bad performance of an algorithm may not be due to fortunate/unfortunate selection of default parameter values. The last point is especially important for studies that compare different algorithms, hence very relevant for this study.

Sequential Parameter Optimization [2] is a framework for surrogate model based optimization that was initially developed for the purpose of parameter tuning of EA's but has since been applied to numerous applications. It is based on methods from Design of Experiment (DoE), Statistics and Machine Learning.

In SPO, an initial DoE is created and evaluated on the target function. The acquired data is used to build a model representing the effects and interactions of the various tuned parameters. In a sequential manner, this model is first exploited to yield new candidate solutions (i.e., parameter settings) and then updated with the data from the new candidates. This is repeated until a stopping criterion is reached, after which a report and analysis of results follows.

In this work, SPO is applied to tune the employed SMS-EMOA and NSGA-II, while MSPO is a competitor to these MO algorithms.

4. EMPIRICAL STUDY

In this empirical study, (M)SPO will be used in form of the SPO Toolbox `SPOT` R-package. This also includes an implementation of the SMS-EMOA, making use of the `emoa` R-package. The NSGA-II implementation stems from the `mco` R-package[1].

4.1 Preliminary Experiment

4.1.1 Setup

In a very first attempt to analyze behavior of the different algorithms, we perform a lengthy optimization of the target function (i.e., the cyclone model) using SMS-EMOA and NSGA-II with default parameters. The goal is to get a reasonably good approximation of the Pareto-front. This will be used to specify a target for the parameter tuning, measured by hypervolume. The default parameters of both algorithms are summarized in Table 2. These parameters are the population size μ, the distribution indexes for crossover η_c and mutation η_m as well as the probabilities for both variation operators p_c and p_m.

Table 2: Default parameters of the employed NSGA-II and SMS-EMOA implementations.

	μ	η_c	η_m	p_c	p_m
SMS-EMOA	100	15	25	0.7	0.3
NSGA-II	100	5	10	0.7	0.2

The optimization run is repeated 50 times, where each run is allowed 100 000 evaluations of the cyclone model. The reference point is chosen to be at PD 5 000 and CE zero. The upper and lower boundary of the COP are listed in Table 3. Please note, that in this work hypervolume will be measured based on the set of non-dominated solutions in an archive of all solutions found during each run, not based on the final population.

Table 3: Lower and upper boundaries of the COP. Based on an example by Löffler [9].

	Da	H	Dt	Ht	He	Be
lower	1134	2250	378	576	540	180
upper	1386	2750	462	704	660	220

4.1.2 Results and Discussion

The maximum hypervolume received from all runs was 3 843.964. Based on this, a target value for the tuning of the algorithms was defined. This was chosen to be 99.9% of the maximum hypervolume, i.e., a value of 3 843.34. Figure 3 depicts the run length distributions of the NSGA-II and SMS-EMOA runs from above. The depicted graphs show the cumulative, empirical probability of the optimization runs reaching the target value over the number of required FE.

[1]All packages are available as open source on `http://cran.r-project.org/`

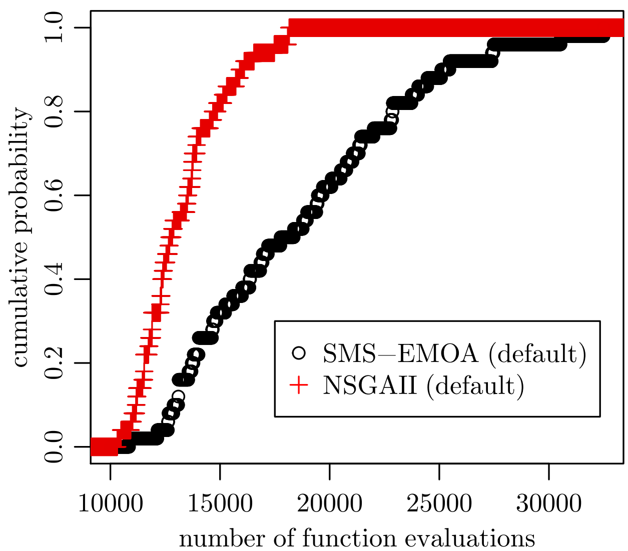

Figure 3: Run length distributons plot for target of 99.9% of hypervolume, i.e., 3 843.34

As can be seen from Fig. 3, all NSGA-II runs featuring standard parameters reached the target after about 17 000 to 18 000 FE, while all SMS-EMOA required about 30 000 FE. NSGA-II provided a much steeper slope than SMS-EMOA, which converges much slower.

The interpretation of results was twofold. On the one hand, the experiments show that both algorithms are able to reach 99.9% of the achievable hypervolume within the maximum budget. Therefore, this value was chosen as a target for the algorithm tuning. The number of FE to reach 99.9% of the achievable hypervolume is minimized. Here, the goal of the tuning is to see how much the value of 17 000 to 30 000 FE could be reduced and whether the results would be applicable for optimization based on CFD models. It is also of interest whether a tuned NSGA-II will still outperform a tuned SMS-EMOA, even though the concerned quality criterion (the hypervolume) is directly optimized by SMS-EMOA.

On the other hand, 1 000 FE or even more seem to be far too much for an optimization invoking expensive CFD models. Therefore, the question is how far, w.r.t. hypervolume, we could possibly get with a strictly limited budget of FE. This was the foundation for additional tuning experiments. Here, the budget is limited to a few hundreds FE and the achieved hypervolume is maximized.

4.2 Tuning

4.2.1 Setup

Table 4 shows the region of interest, i.e., the lower and upper boundaries between which parameters are varied during tuning. The upper boundary of μ is chosen to coincide with the smallest tuning budget, i.e., 120.

First, the algorithms were tuned to reach the previously determined target value from above, minimizing the number of required FE. This tuning task will be referred to as

Table 4: Region of interest in which parameters are tuned.

	μ	η_c	η_m	p_c	p_m
lower	3	0	0	0	0
upper	120	40	40	1	1

minimization of the required FE to reach the Target hypervolume (FTar). Additionally, both algorithms were tuned to reach a maximum hypervolume for a strictly limited budget of FE. This reflects the real world problem where only a certain budget is available for the optimization process. The budgets chosen were 120, 240, and 500 function evaluations. This second set of tuning runs will be referred to as Achieved Hypervolume maximization (AHvol). Thus, each algorithm is tuned four times, resulting into an overall number of 8 tuning runs.

SPO is utilized to tune the algorithms, but also has a large number of parameters:

- A Kriging model based on code by Forrester et al. [7] was used as a surrogate model.
- The number of algorithm runs in each tuning run are limited to 500 (for the fixed target value) and 1 000 (for the fixed budgets).
- In the initial design, each parameter setting is evaluated twice (fixed target) or four times (fixed budget).
- Each parameter setting may be re-evaluated no more than ten (fixed target) or twenty (fixed budget) times.
- In each sequential step, one new solution is evaluated on the target function and one old solution may be re-evaluated.
- The number of re-evaluations of promising solutions are increased linearly. Optimal computing budget allocation is not used.
- The initial design consists of 100 different parameter settings.
- The sequentially created models are optimized by Latin Hypercube Sampling (LHS) and Differential Evolution (DE) [14].
- The sequential step LHS evaluates 1 000 points on the model.
- The sequential step DE uses 2 000 evaluations and a population size of 50.

The larger numbers for the tuning under limited budgets is supposed to amend the higher noise level caused by small budgets.

At the end of each tuning run, resulting parameter sets are compared to default parameters. In addition to the comparison of tuned and default parameters, a model-based optimization is performed with multi-objective SPO. Here, a Kriging model is used as a surrogate for each objective. A maximum of 120 evaluations was allowed, which is a reasonably low budget for real world problems. The initial design consisted of 30 points. The surrogate is optimized with SMS-EMOA using default parameters and suggesting 10 points for evaluation in each sequential step. No repeated evaluations are performed, since the presented COP is deterministic. Note that, in contrast to NSGA-II and SMS-EMOA MSPO was not tuned.

4.2.2 Results and Discussion

The determined sets of tuned parameters are combined in Table 5. The suffix "Ftar" indicates parameters tuned with respect to minimum required FE to reach the 99.9% target hypervolume (case FTar from above). The results from tuning with limited budgets of 120, 240, or 500 FE are indicated by the suffix consisting of "B" and the corresponding number. Results within this table differ remarkably.

Table 5: Results of the eight tuning runs. Parameters of the best found solution are shown.

	μ	η_c	η_m	p_c	p_m
SMS-EMOA-Ftar	12.44	18.03	3.59	0.25	0.37
SMS-EMOA-B500	3.01	1.63	0.14	0.02	0.54
SMS-EMOA-B240	3.19	10.20	0.00	0.00	0.56
SMS-EMOA-B120	3.14	12.48	0.09	0.01	0.98
NSGAII-Ftar	43.04	39.09	0.11	0.45	0.25
NSGAII-B500	5.05	21.92	0.03	0.31	0.41
NSGAII-B240	3.11	17.99	0.04	0.08	0.53
NSGAII-B120	3.05	18.46	0.27	0.01	0.70

In the case of FTar, where large numbers of FE are allowed, optimal population sizes are much larger than in the case of AHvol, where the budgets are rather small. The population size is 4 times larger for SMS-EMOA and around 10 times larger for NSGA-II. Moreover, recombination plays a stronger role in case of FTar, marked by a probability of at least 0.25. For AHvol optimization, the recombination probability exceeds 0.25 in only one case, i.e. NSGA-II-B500. The mutation probability has negative correlation with the recombination probability. Thus, it is smallest where the budget is largest. It reaches nearly 100% for SMS-EMOA-B120 indicating that for smallest budgets mutation plays a much more important role than recombination.

The outlier in recombination probability (NSGA-II-B500) coincides with an unusual population size. Here, population size is five individuals, while all other AHvol cases yield an optimal population size of three individuals.

Compared to the default values, η_m was reduced remarkably, indicating that small parameter changes are preferred. On the other hand, η_c varies strongly in the given interval. The SPO Kriging model also attributed a low importance to this parameter.

Figure 4 depicts the run length distribution plots for the considered algorithms featuring standard as well as tuned parameterizations. Here, different random number generator seeds are used for initialization to prevent bias introduced by the choice of seeds during the tuning. Due to this, the results featuring standard parameterization look a bit different although they stem from the same parameterizations.

A clear improvement can be observed comparing standard and tuned parameterization. All runs with tuned parameters reach the optimization goal much earlier, i.e. SMS-EMOA after 4 100 FE compared to NSGA-II after 8 130 FE (cf. Table 7 for the concrete numbers). Interestingly, SMS-EMOA performs better than NSGA-II comparing the tuned variants, while the algorithms behave vice versa considering the standard parameterizations. Note that the slopes for cumulative probabilities for both algorithms are much larger for the tuned variants as well.

The received hypervolume values for the AHvol tuning are depicted in Table 6. Next to mean and standard deviation ("SD"), the table lists minimum and maximum values ("Min." and "Max." resp.) as well as "Mean%" being the mean percentage of achieved hypervolume. Corresponding boxplots are provided in Fig. 5. It can be observed that the

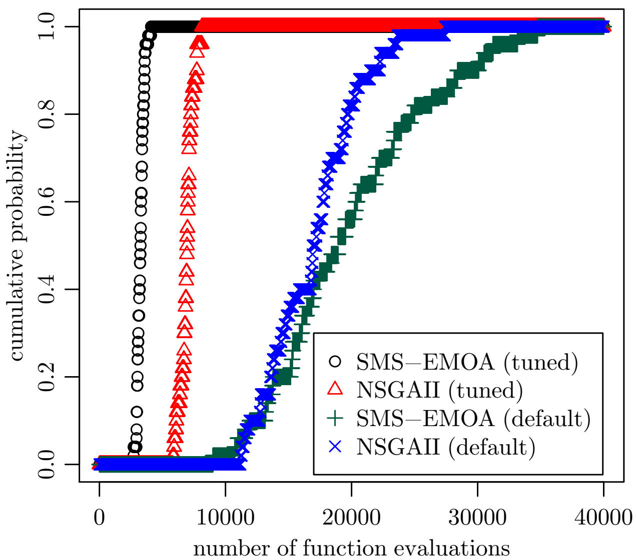

Figure 4: Run length distribution plot for target of 99.9% of hypervolume, i.e., 3 843.34. Showing results for default algorithm parameters as well as tuned to reach the target hypervolume with minimum number of function evaluations. Based on validation experiments with new random seeds.

tuned instances are significantly better than the ones featuring standard parameterizations. Moreover, the expected behavior that performance increases with increasing budget, can be retraced in the data.

Even with only 120 FE both algorithms capture about 90% of achievable hypervolume in the mean. Doubling this budget yields an increase up to 97% and having 500 FE allowed, more than 99% of hypervolume is achieved. These results can only be topped by MSPO, which is able to achieve over 99% hypervolume within only 120 FE.

Table 6: Resulting hypervolumes for default algorithm parameters (.def) as well as tuned parameters. Based on validation experiments with new random seeds on COP1.

	Min.	Mean%	Mean	Max.	SD
SMS.def.120	3517.5	64.2	3620.5	3719.5	43.2
NSG.def.120	3488.8	63.2	3614.6	3707.4	43.2
SMS.120	3687.3	87.2	3764.4	3811.9	33.1
NSG.120	3724.4	91.6	3791.7	3823.4	22.4
SMS.def.240	3574.6	74.4	3684.3	3764.4	41.9
NSG.def.240	3559.0	70.9	3662.4	3733.4	40.4
SMS.240	3802.2	97.4	3827.7	3835.7	7.1
NSG.240	3794.6	97.4	3827.7	3834.7	6.5
SMS.def.500	3688.2	84.5	3747.6	3794.2	27.2
NSG.def.500	3651.8	83.2	3739.1	3788.3	31.1
SMS.500	3834.7	99.1	3838.2	3839.6	1.1
NSG.500	3835.3	99.0	3837.5	3839.3	0.9
MSPO.120	3841.0	99.6	3841.5	3841.9	0.2

It was found that solving a COP with the considered algorithms produces a strong need for parameter tuning. Within all the received results, the performance of the tuned variants is much better than the performance of the default ones.

It turned out that a population size of three is optimal in almost all cases where a very small budget was imposed. Moreover, mutation is the more important variation operator and prefers rather small changes. Considering the case of FTar, the number of required FE was reduced to around 4 000 (from over 25 000).

If surrogate models are allowed, results further improved dramatically. MSPO proved to be the best performing algorithm in our study achieving more than 99.5% of possible hypervolume within only 120 FE.

A basic validation of results has already been performed using different random number generator seeds.To further validate our findings w.r.t. modeling, an alternative model for CE is considered, i.e., COP2. The following section will present experimental results for this second problem and compare them to COP1.

4.3 Validation

4.3.1 Setup

To validate results achieved by tuning on COP1, performance of tuned and default parameters are compared on COP2. Thus, tuned parameters are tested on a previously unseen problem instance. During validation, all algorithms are run 50 times to create statistically sound results.

Results of the two models for CE will differ. In general, the second model (COP2) does predict better CE. As the reference point remains unchanged, hypervolumes are expected to be larger for COP2. They should only be compared in terms of relative performance between algorithms, no absolute comparisons between hypervolumes of different models should be made.

4.3.2 Results and Discussion

Based on COP2, a new target hypervolume value had to be determined. A hypervolume value of 4 040.639 has been received as the maximum value. 4 039,479 represents the 99.9% target hypervolume.

Table 7: Number of FE required for all 50 of 50 runs to reach the target hypervolume (COP1: 3 843.34, COP2: 4 039.479). Based on the validation with different seeds optimizing hypervolume on COP1 as well as COP2.

	SMS.tun	SMS.def	NSG.tun	NSG.def
COP1	4100	34750	8130	27410
COP2	2830	18710	4390	18040

Table 7 summarizes the number of FE required to reach the target hypervolume. For COP2, all these values are smaller than the ones for the corresponding algorithmic variants for COP1. This reveals that COP2 may be a bit easier to solve than COP1.

Considering the influence of tuning, we were able to recapitulate the results received for COP1: the tuned variants perform much better than the ones featuring standard parameterizations. For all SMS-EMOA runs on COP2, only less than 3 000 FE were necessary to reach the target hypervolume. These results are also reflected in the corresponding run length distribution plots in Fig. 6.

Table 8 as well as Fig. 7 present the direct comparison of default and tuned parameter settings. These data supplement the results received for COP1 as presented in Table 6 and depicted in Fig. 5.

Again, the tuned variants perform much better than the ones featuring default parameters and results improve with larger budgets. For COP2, the algorithms were able to

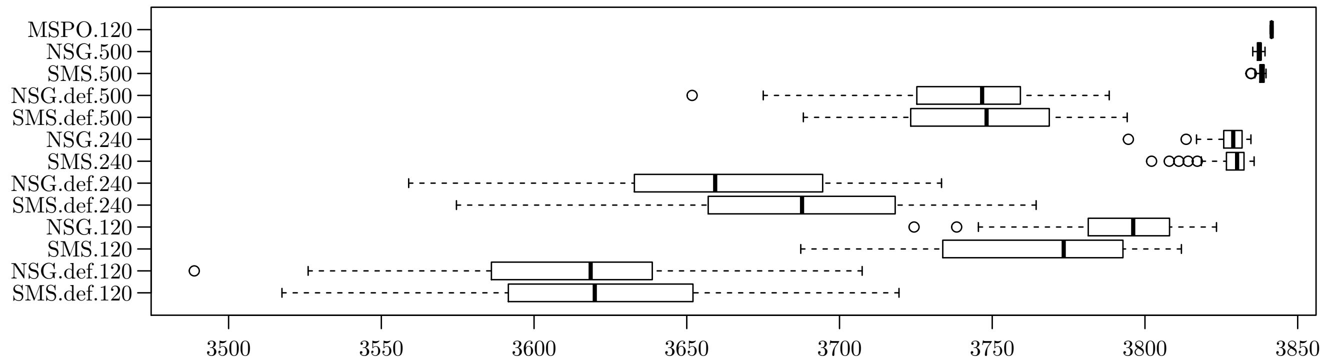

Figure 5: Boxplot of hypervolume for default algorithm parameters (.def) as well as tuned parameters on COP1. Based on validation experiments with new random seeds.

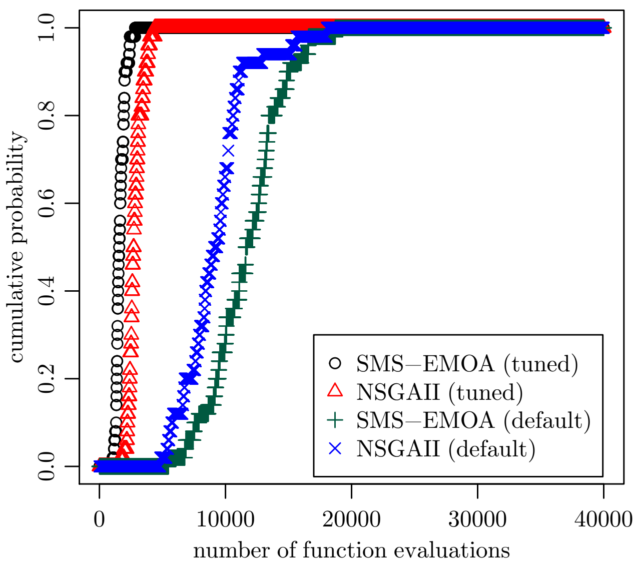

Figure 6: Rld plot for target of 99.9% of hypervolume, i.e., 4 039.479. Showing results for default algorithm parameters as well as tuned to reach the target hypervolume with minimum number of function evaluations. Based on validation experiments with COP2.

achieve around 95% of the maximum hypervolume within only 120 FE. This indicates a faster convergence on COP2 compared to COP1 as can also be observed in Table 7 and the corresponding run length distribution plots (cf. Fig. 6).

Also, for COP2, the algorithmic instances with the largest allowed budget (500 FE) were able to perform as good as the MSPO algorithm with only 120 FE. To be precise, they performed slightly better with respect to the mean values and standard deviations. Nevertheless, MSPO used much less FE and, thus, is preferable for expensive target functions.

Interestingly, NSGA-II seems to perform a bit better than SMS-EMOA when the optimization runs are limited to very small budgets. While the run length distributions indicate that SMS-EMOA performs better in the long run, NSGA-II excels for the smallest budget of 120 FE, both for COP1 and COP2

The results received for the COP were validated incorporating a different model for CE. We were able to show that optimized parameter values received for one model could be

Table 8: Resulting hypervolumes for default algorithm parameters (.def) as well as tuned parameters. Based on validation experiments with COP2.

	Min.	Mean%	Mean	Max.	SD
SMS.def.120	3691.6	82.3	3835.7	3929.5	47.9
NSG.def.120	3691.6	82.9	3842.7	3936.6	53.5
SMS.120	3892.0	94.7	3979.0	4029.6	34.6
NSG.120	3845.6	97.2	4007.9	4032.8	28.3
SMS.def.240	3777.2	85.5	3872.9	3954.1	42.1
NSG.def.240	3794.9	87.1	3890.7	3951.2	37.4
SMS.240	4018.4	99.3	4032.9	4038.8	5.1
NSG.240	4019.6	99.4	4033.5	4038.0	4.2
SMS.def.500	3879.0	92.1	3948.6	4025.0	34.8
NSG.def.500	3893.6	92.2	3950.4	4001.6	25.8
SMS.500	4035.6	99.8	4038.9	4039.5	0.8
NSG.500	4036.6	99.8	4038.7	4039.3	0.5
MSPO.120	4034.7	99.8	4038.6	4039.8	1.2

successfully transferred to the same optimization task incorporating a different model. This is a strong result for our aim to determine optimal parameter settings for industrial optimization problems. This may warrant to tune parameters with cheap models, and later apply the tuned parameters to a model where tuning would be too expensive.

5. SUMMARY AND OUTLOOK

This paper investigates the cyclone (dust separator) optimization problem. After describing the problem itself, objectives, and parameters, algorithms for solving this problem are presented. These algorithms are first tested with their default parameter settings. Afterwards, the algorithms' parameters a tuned under different specifications. Firstly, a target hypervolume value is specified and the algorithms are tuned to require as few FE as possible. Secondly, very small budgets were imposed and the algorithms were tuned for a best performance w.r.t. hypervolume. Finally, results have been validated implementing an alternative model for one of the objectives.

It is found that tuned algorithm parameters perform much better than the default settings. The results for a fixed FE' budget point to a certain parameterization with a population size of three and a mutation dominated variation that promise good results for further investigations, particularly incorporating more complex simulation models.

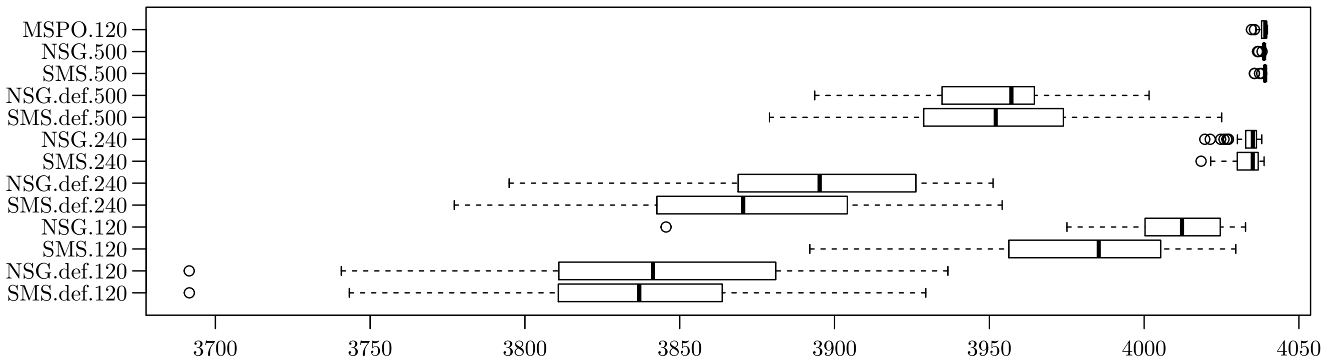

Figure 7: Boxplot of hypervolumes for default algorithm parameters (.def) as well as tuned parameters. Based on validation experiments with COP2.

Moreover, the surrogate model based MSPO approach with a very limited budget of FE performed extremely well in our comparison. Therefore, this strategy will be investigated in more detail in future research. Further research directions w.r.t. MSPO could concern the choice of model, optimization technique, or infill criteria.

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